2021 International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON)
Pune, India. Oct 29-30, 2021

2021 International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON) | 978-1-6654-2503-2/21/$31.00 ©2021 IEEE | DOI: 10.1109/SMARTGENCON51891.2021.9645853

Diagnosis of Parkinson's Disease Using Deep Neural Network Model

Anila M
Assistant Professor,
Dept of CSE, Koneru Lakshmaiah Education Foundation,
Vaddeswaram, Andhra Pradesh, India
anilarao.m@gmail.com

Pradeepini G
Professor,
Dept of CSE, Koneru Lakshmaiah Education Foundation,
Vaddeswaram, Andhra Pradesh, India
pradeepini_cse@kluniversity.in

***Abstract*— Parkinson's disease is a neuro-degenerative disorder that effects central nervous system and is observed in many people worldwide. PD diagnosis is complex for the clinicians as it requires meticulous analysis of the patient. Though there are many characteristics and symptoms that indicate the disease, voice characteristics play a major role among the predictive characteristics. Person with PD experiences several vocal degradations like shaky and low speech. Voice analysis offers the additional benefit of being non-invasive, low cost and simple to diagnose. Many enthusiastic and great researchers have created new models and improved existing models in this area, and there is a vast amount of research in this field all over the world. We created an optimized Deep neural network (which is referred as Opt-DNN in rest of the paper) model and compared it to various algorithms such as random forests, SVM, XG Boost, and KNN in this paper. Among all the algorithms used, the proposed model turned up to be the best algorithm with accuracy 95.14.**

Keywords— Parkinson's Disease, Neural Network, K-Nearest Neighbor Principal Component Analysis, Random Forest.

I. INTRODUCTION

Parkinson's disease is a progressive neurodegenerative condition that affects mostly senior citizens. The cause of Parkinson's disease is unclear, but if the disease is diagnosed at early stage, the symptoms can be alleviated. Majority of the studies revealed that people with Parkinson's disease had voice problems. As a result, voice data can be used to diagnose Parkinson's disease.

PD affects millions of people, according to the American Parkinson Disease Association, and causes severe health problems. Even though people with Parkinson's disease show a wide range of symptoms, determining the root cause remains difficult. People over the age of 50 are more likely to develop this disease early because their bodies are more susceptible to degenerative diseases. PD is caused by a lack of dopamine or a decrease in dopamine levels, which makes motor movements difficult. PD symptoms are divided into two categories: motor symptoms and non-motor symptoms, clinical tests of motor symptoms are used to diagnose the disorder. Most patients with Parkinson's disease have vocal impairments, which are referred to as dysphonia. The key characteristic used to diagnose the presence of PD is dysphonia.

The diagnosis of Parkinson's disease at an early stage is a difficult challenge for doctors because the symptoms intensify and affect the individual day by day. Many researchers in this area have conducted comprehensive surveys and developed numerous models for detecting Parkinson's disease. [7]created a model that used a combination of SVM and a gaussian Radial basis kernel function to predict PD with a 91.4 percent accuracy. [8]have done a comparison of regression tree, decision tree, and ANN and found that ANN produces better results. [9] proposed a multi-class classifier with an accuracy of 89.47 percent, as well as a new collection of measures and a different strategy for selecting features. [10] introduced a fuzzy-based transformation approach that was combined with an SVM classifier to achieve a 93.47 percent accuracy. For successful classification, it is critical to practise feature selection to select the most important attributes[11].

Aim of this paper is to develop an optimised Deep Neural Network Model for classification of PD. We proposed , an optimal DNN-model including PCA for attribute selection. Rest of the paper is organised as follows: various aspects and results achieved by other authors is discussed in Section 2. Then we presented our Proposed methodology in Section 3 along with metrics and Section 4 deals with experimental set-up , results, and discussions . The next section includes future scope and conclusions.

II. LITERATURE SURVEY

The analysis for Parkinson's disease diagnosis using voice dataset is discussed in [1]. The speech dataset is analysed using a variety of machine learning algorithms. The speech dataset includes the voice frequencies of 31 Parkinson's disease patients. NN shows highest accuracy of all algorithms, while random forest has a decent accuracy and Naive Bayes has the lowest accuracy for disease detection.

The author proposed a hybrid intelligent framework for predicting disease progression in the paper [2], which used unique methods to eliminate noise, a clustering method to define class labels, and prediction methods to predict disease progression. PCA is used to determine which dimensions are the most important. Later on, support vector regression approaches and neuro fuzzy interface systems are used. This hybrid intelligent system significantly improved the accuracy of Parkinson's disease prediction. Using deep neural networks on speech datasets, the severity of the disease can be predicted [3]. Tensor flow is a deep learning library that is used to implement artificial neural networks to predict the state of Parkinson's disease.

The experiment was evaluated using standard methods for separating a healthy person from a person with Parkinson's disease by detecting dysphonia in this paper[4]. PPE (Pitch Period Entropy), a new measure of dysphonia, is added. This procedure has been found to be reliable and has revealed only a few perplexing results. The ability to distinguish healthy people from people with Parkinson's disease has been demonstrated using a kernel SVM approach in conjunction with conventional methods. The use of dysphonia measurements for early diagnosis in telemonitoring of Parkinson's disease is discussed[5]. The study's aim is to find the smallest subset of features that are important to PD score. This method yielded two scores to denote the test sample, i.e., an individual with Parkinson's disease or a healthy person. To optimise prediction generalisation, a model with minimal bias was also used. To construct learning functions based on characteristics, a combination of the expectation maximisation algorithm and genetic programming (GP-EM) is used in this paper[6]. To fit the data as a modular structure, the transformed data is modelled as a Gaussian mixture using EM. This allows us to determine whether or not an individual has Parkinson's disease..

Genetic Algorithm, Wavelet Kernel, and Extreme Learning Machines are used in the proposed solution. For classification, an ELM learning approach is used to train a single layer neural network. In the WK-ELM structure, WK has three customizable parameters. The number of hidden neurons chosen in the architecture had a significant impact on ELM output. To find the best values for these parameters and the number of hidden neurons in ELM, a genetic algorithm was used. A few metrics, such as sensitivity, accuracy, and ROC curves, are used to evaluate the proposed method's efficiency.

One of the most cost-effective strategies for diagnosing people is to use a Deep Belief Network[8]. The DBN is capable of diagnosing Parkinson's disease by separating and analysing patients' speech data. After the most important features have been detected, the DBN is used to establish a pattern and fit voice samples. DBN uses two stacked Restricted Boltzmann Machines (RBMs) and an output layer to classify PD. Since the initial weights are random, the RBM technique is used in unsupervised learning. The fine-tuning is done with Back Propagation. The proposed system's efficacy is assessed by contrasting experimental findings with different methodologies.

The optimal solution to the problem of Parkinson's disease is identified in this paper[9], which involves three major steps and a novel Multiple Feature Evaluation method. The proposed approach uses a multi-agent scheme with five classification techniques: Naive Bayes, Decision Tree, Neural Network, Random Forest, and SVM. The 10-fold-CV is used to measure process learning and monitor performance differences. The results show that MFEA identifies the best set of attributes and thus improves classifier efficiency.

They used an incremental support vector machine to estimate the Unified Parkinson's Disease Rating Scale in this paper[10] (UPDRS). The aim of this approach is to minimize the amount of time needed to diagnose Parkinson's disease and improve the performance. The study's key findings are that the approach incorporates reducing dimensions/features, clustering techniques, and improved PD prediction accuracy while reducing computation time.

The author of this paper[11] used speech impairments to predict Parkinson's disease. The earliest symptom of this condition is a loss of voice. As a result, the author proposed a DNN classifier with stacked autoencoder as well as a SoftMax classifier to predict it. They used two separate datasets for this study. The dataset contains the "Parkinson Speech Dataset with Several Types of Sound Recordings (PSD)" and "Oxford Parkinson's Disease Detection (OPD)" datasets to differentiate between individuals with PD and those who are not. Deep neural networks achieve a 94 % accuracy rate.

To predict Parkinson's disease, various machine learning methods such as SVM, linear discriminant analysis (LDA), regression trees (RT), k Nearest-Neighbors (k-NN), naive Bayes (NB), Radial Basis Function-Neural Networks (RBF-NN), and Mahalanobis distance classifier are used. The SVM classifier had the best overall results. SVM achieves a 92.7% accuracy rate[12]. Feasible study done by us is given in the Table 1 containing information of authors and their methodologies.

TABLE I. LITERATURE SURVEY OF VARIOUS METHODOLOGIES DEVELOPED, ENHANCED FOR DIAGNOSIS OF PD.

S.No	Author	Year	Methodology
1	Marius Ene	2008	Probabilistic neural network
2	Chien-Wen Cho	2009	PCA with LDA
3	Max A. Little	2009	Support Vector Machine
4	Resul Das	2010	Decision Tree and Regression , Neural Networks, DMneural
5	C. Okan Sakar & Olcay Kursun	2010	SVM
6	Ipsita Bhattacharya	2010	LibSVM , kernel functions
7	Freddie Åström	2011	Parallel Neural network with reduced error rates
8	Athanasios Tsanas	2012	Speech signal processing algorithms, RF,SVM
9	Hui-Ling Chen	2013	FKNN,SVM
10	Mohammad S Islam	2014	Random Tree (RT), Support Vector Machine (SVM) and Feedforward Back-propagation based Artificial Neural Network (FBANN)
11	Oana Geman	2014	Space-time nonlinear adaptive system,Multi-state Markov Model
12	R. Prashanth	2016	Naïve Bayes, Support Vector Machine (SVM), Boosted Trees and Random Forests classifiers
13	Zachary C.Lipton	2016	MLP, Long Short-Term Memory (LSTM-RNN) with forget gate.
14	Ali H. Al-Fatlawi	2016	Deep belief network, Restricted Boltzmann Machines ,Back propagation

15	Indrajit Mandal	2017	Multinomial logistic regression, rotation forest together with SVM and PCA, ANN, boosting methods
16	Erika Rovini	2018	SVM, RandomForest, NaiveBayes
17	Haijun Lei	2018	A least square regression model based on the Fisher's linear discriminant analysis (LDA) and locality preserving projection (LPP)
18	Shreya Bhat	2018	Neuroimaging modalities used together with advanced machine learning techniques
19	Leandro A. Passos	2018	ResNet-50 , Optimum-Path Forest (OPF) classifier
20	Lígia Sousa	2019	deep neural network, a K-nearest neighbour algorithm,principal component analysis for feature selection
21	Carlos Castro	2020	Multiple Neural Networks were trained to vary the number of neurons in the hidden layer between 10 and 6000 in steps of 10
22	Nancy Noella R S	2020	Artificial Neural Network (ANN) for the diagnosis of PD using Positron Emission Tomography (PET) scanned images.

III. PROPOSED METHODOLOGY

There are two important steps in our proposed method. The following sub sections clearly describe the process.

First sub-section is made to explain importance of data visualisation and the later sub-section presents the proposed approach of diagnosing PD.

A. Data visualisation:

It is always necessary to have knowledge of our data, as this allows us to obtain all the information of our dataset . Data visualisations will reveal new perspectives to those who are unfamiliar with the data, as well as communicate conclusions to those who may not see the raw data. We used a dataset from the University of California, Irvine (https://archive.ics.uci.edu/ml/index.php). with a total of 31 records of people, 23 of whom are affected and 8 are not. The participants were between the ages of 46 and 85. Everyone gave an average of six sustained vowel "ahh..." phonation's, ranging in length from one to 36 seconds [13], for a total of 195 samples. Different measures were applied to each recording, resulting in 22 real-value features. The last attribute(23rd feature) in the dataset shows the patient's condition, i.e., 0-represents a stable patient and 1-represents a patient with Parkinson's disease. The following table 2 lists the features and their descriptions. Each feature is calculated with max values, min values, Mean and Standard Deviation.

TABLE II. FEATURE DESCRIPTION FROM DATASET USED AND THEIR MAX VALUES, MIN VALUES, MEAN AND STANDARD DEVIATION

Sno	Feature Name	Min Value	Max Value	Mean	SD
1	MDVP:F0 (Hz)	88.33	260.105	154.229	41.39
2	MDVP:Fhi (Hz)	102.145	592.03	197.105	91.492
3	MDVP:Flo (Hz)	65.476	239.17	116.325	43.521
4	MDVP:Jitter(%)	0.002	0.033	0.006	0.005
5	MDVP:Jitter(Abs)	0	0	0	0
6	MDVP:RAP	0.001	0.021	0.003	0.003
7	MDVP:PPQ	0.001	0.02	0.003	0.003
8	Jitter:DDP	0.002	0.064	0.01	0.009
9	MDVP:Shimmer	0.01	0.119	0.03	0.019
10	MDVP:Shimmer(dB)	0.085	1.302	0.282	0.195
11	Shimmer:APQ3	0.005	0.056	0.016	0.01
12	Shimmer:APQ5	0.006	0.079	0.018	0.012
13	MDVP:APQ11	0.007	0.138	0.024	0.017
14	Shimmer:DDA	0.014	0.169	0.047	0.03
15	NHR	0.001	0.315	0.025	0.04
16	HNR	8.441	33.047	21.886	4.426
17	RPDE	0.257	0.685	0.499	0.104
18	D2	0.574	0.825	0.718	0.055
19	DFA	-7.965	-2.434	-5.684	1.09
20	Spread1	0.006	0.45	0.227	0.083
21	Spread2	1.423	3.671	2.382	0.383
22	PPE	0.045	0.527	0.207	0.09

We have represented boxplots, in figure 1, for every feature for visualisation of data. Boxplot also known as whisker-plot is a five-point summary of data distribution (minimum, first quartile (Q1), median, third quartile (Q3), and "maximum"). It can give us information about the outliers and their values. It can also tell us whether our data is symmetrical, and whether data is skewed.

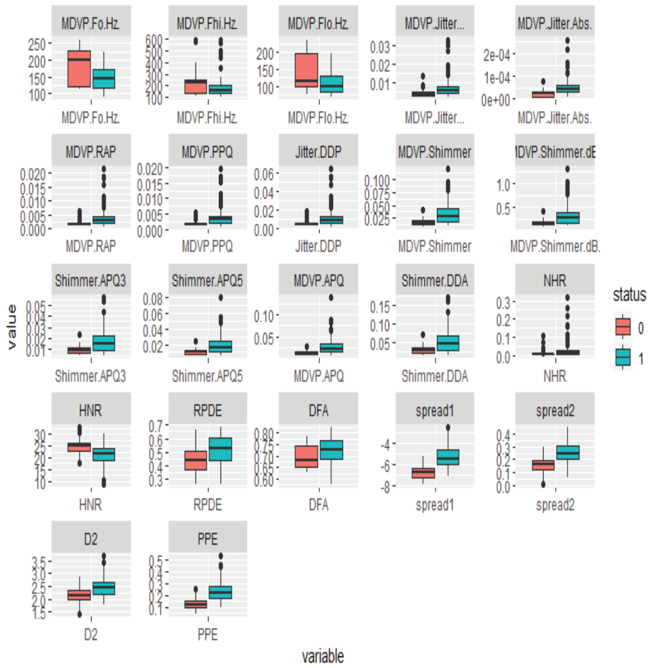

Fig. 1. Boxplots for Features in the PD voice Dataset.

B. *Methodology*

The basic step is to choose a desired model by the construction of a Neural Network Architecture. To do so, we have done the following:

a) Load dataset, the features extracted from voice recordings of the patients.
b) Perform pre-processing to remove noisy data if any
c) Apply PCA to extract most-relevant features. PCA is relied on the assumption that only those features with the good variance contain the information about certain classes.
d) Implement ML algorithms like KNN, RandomForest, SVM and XGBoost with proposed algorithm.
e) Compare accuracies of all algorithms.
f) Assessment of Model is done with various metrics.

Neural Network contains three layers, one input layer, one output layer and one or more hidden layers. The input layer is usually the first layer in a Neural Network. As it can be observed from design of Figure 2, each input layer comprises of several nodes. Each node represents input feature and the links between input node and hidden layer node reflects the weight of the input feature. At each hidden unit, product of input feature and its respective weight is calculated and is sent to next hidden layer, and to final output layer will apply activation function to give prediction.

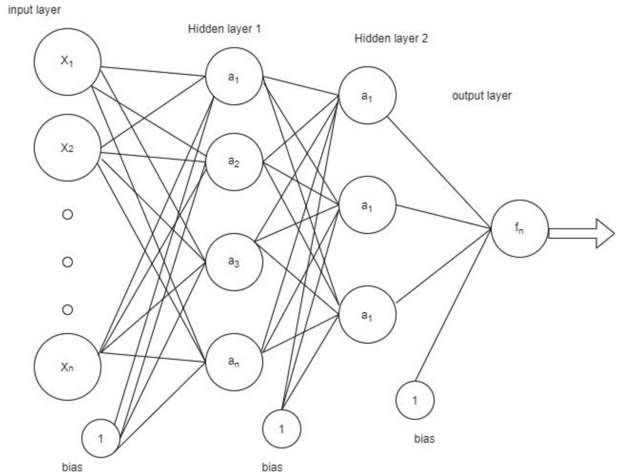

Fig. 2. Architecture of Neural Network

The contribution to the work is represented by the weights. We took 17 of the available features out of the total of 22, as they are extracted after PCA. The layers between the input and the output layer are called hidden layers.

Construction of Neural Network architecture for the Binary classification of PD is done as below.

a) Design the Neural Network with the criteria: Number of input features, Number of Hidden Layers, Number of neurons in each Hidden Layer, Class labels.

b) Execute the DNN with hyperparameter tuning, record the accuracy, freeze the architecture for further implementation.

As a part of Data pre-processing, each attribute/feature is checked with presence of missing or null values and when it is done while implementation of our code, it is observed that no such values are existing, and it can be seen in the following figure 3. So, we continued our proposed methodology with design of our own Neural Network with hyperparameter tuning.

```
> na = colSums(is.na(park))
> na
              name        MDVP.Fo.Hz.
                 0                  0
 MDVP.Jitter.Abs.           MDVP.RAP
                 0                  0
  MDVP.Shimmer.dB.       Shimmer.APQ3
                 0                  0
               NHR                HNR
                 0                  0
           spread1            spread2
                 0                  0

   MDVP.Fhi.Hz.     MDVP.Flo.Hz.   MDVP.Jitter...
              0                0                0
       MDVP.PPQ       Jitter.DDP     MDVP.Shimmer
              0                0                0
   Shimmer.APQ5         MDVP.APQ      Shimmer.DDA
              0                0                0
         status             RPDE              DFA
              0                0                0
             D2              PPE
              0                0
```

Fig. 3. Features of data set when checked with missing or null values.

Following figure 4 depicts flow of proposed methodology, Opt-DNN.

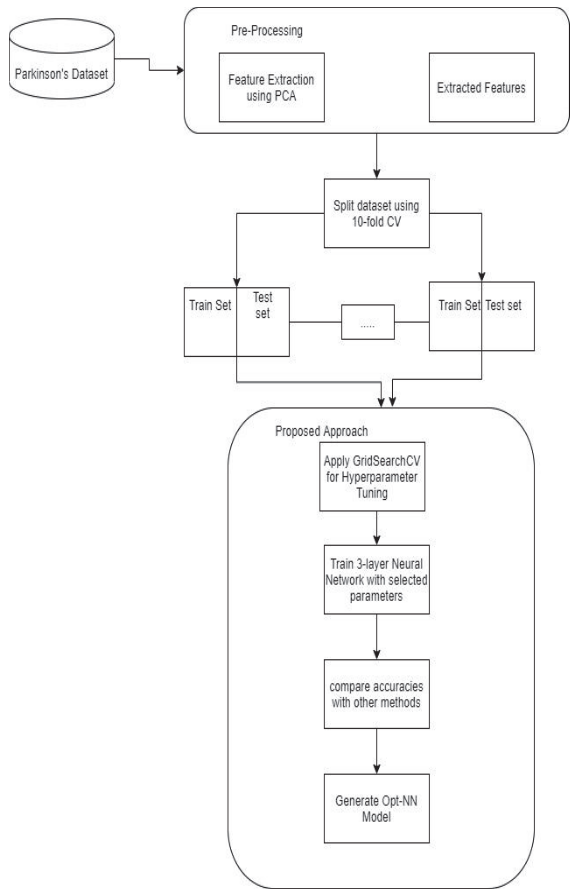

Fig. 4. Proposed Opt-NN approach

To ensure that most relevant features are extracted we have used Priciple Component Analysis. PCA is an unsupervised statistical methodology for examining the relationships between a group of variables. It helps reducing the number of variables in a data set while retaining as much data as feasible when the dataset is of higher dimensions. Here, we used it for the purpose, to make sure the most important features are identified so that we get better accuracy than existing models. The following Figure 5 depicts the importance levels of features, out of 22 features (23^{rd} feature being representing status/label), 17 features are extracted. On X-axis , it is feature number and y-axis , feature importance are specified.

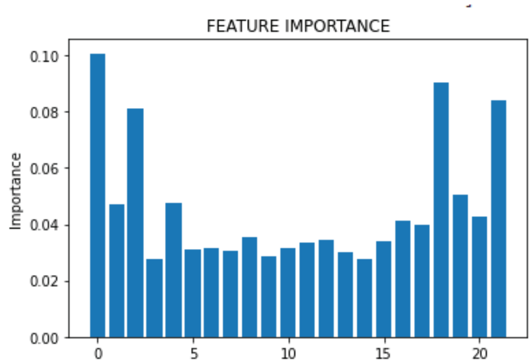

Fig. 5. Feature importance after applying PCA

After feature extraction and selection, Opt-DNN is implemented in comparison with various machine learning algorithms like KNN, RandomForest, SVM and XGBoost are applied. Implementation of algorithms is performed using python in Google colab notes(https://colab.research.google.com). For hyperparameter tuning and setting up the architecture of Optimised Neural Network, we have used GridSearchCv method for selecting hyperparameters and the setting of those values returned by the method as given in the table 3, which when considered and implemented our model, achieved better accuracy than other existing models. As part of optimizer , SGD is used. In each iteration, SGD selects one data point at random from the whole data collection, thereby reducing computations.

Neural Network with hyperparameter tuning is done as follows:

TABLE III. HYPERPARAMETER SETTING

Number of Hidden Layers	3
Number of Neurons in Hidden Layer	50,180,546
Epochs	100
Batch sizes	15
Activation function	ReLu(Hidden Layers), sigmoid(Output Layer)
Optimizers	SGD
Learning rates	0.01
Performance metrics	Accuracy,MSE, MAPE,F1,Recall,Precision
Cross-validation	10

IV. RESULTS AND DISCUSSIONS:

We have used Python programming in Google colab for implementation of proposed methodology. We first used PCA analysis to the data set because it eliminates certain redundant features and allows for maximum variation with no effect on performance of the model. We used a variety of algorithms in this experiment, including Artificial Neural Networks, Random Forest, SVM, XG-Boost, and KNN.

To assess the performance of Opt-DNN various metrics like Accuracy(ACC), precision, recall, f1-score MSE and MAC are recorded as calculated in the implementation. For every model confusion matrix is created and the values represent , TP is the number of true positives, FN means the number of false negatives, TN represents the true negatives, and FP is the false positives. These four values from confusion matrix are used to determine the metric values. Structure of confusion matrix is given as below in Table 4.

TABLE IV. CONFUSION MATRIX

		Actual Values	
		Positive	Negative
Predicted Values	Positive	TP	FP
	Negative	FN	TN

TABLE V. VARIOUS METRICS RECORDED FOR ML TECHNIQUES.

Algorithm	ACC	Precision	F1-score	Recall	MSE	Mean Absolute Classifier
Opt-DNN	95.14	0.9484	0.9484	0.9491	0.0508	0.0508
RF	91.52	0.9237	0.9082	0.9152	0.0847	0.0847
SVM	93.22	0.9375	0.9268	0.9322	0.0677	0.0677
XG Boost	88.13	0.8850	0.8829	0.8813	0.1186	0.1186
KNN	86.44	0.8564	0.8590	0.8644	0.1355	0.1355

After observing above results in the table 4, and according to the steps mentioned in proposed method, our proposed approach Opt-Deep Neural Network achieved high accuracy than other ML techniques implemented and the same can be observed from Figure 5, which is constructed to depict scores of various metrics for proposed model with other mentioned Algorithms.

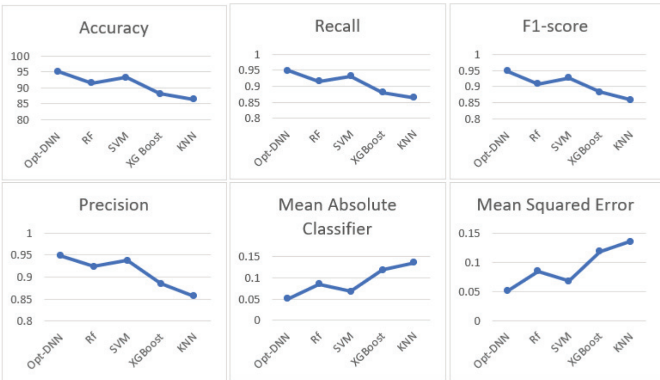

Fig. 6. : comparison of metrics

V. CONCLUSION

Parkinson's disease (PD) is a neurodegenerative ailment that affects the neurological system of the aged, with symptoms that progressively worsen. The condition is detected in this study by analysing the voice data of persons with Parkinson's disease. Random Forest, KNN, SVM, and XG Boost are some of the machine learning algorithms utilised for this. For all the models employed, error rates are determined, and performance measures are analysed to classify the best model. Accuracy, f1-score, recall score, precision score, confusion matrix, and classification report are among the measures. With an accuracy of 95.14%, precision of 0.9484, and a f1-score of 0.9484, Opt-DNN emerges as the best model among all the other ML approaches.

VI. LIMITATIONS

With the implementation of our proposed DNN, it is limited to only three hidden layers. For small datasets, this sort of neural network with three hidden layers is sufficient and efficient. We have utilised one feature selection strategy, which minimises the amount of features and extracts the most important ones.

VII. FUTURE DIRECTION

This study could be improved even more by including multiple feature selection processes into classification systems. Additional layers in the Neural Network can also be beneficial for learning complex representations. The number of neurons in the hidden layers is also a significant consideration when deciding on the overall neural network architecture. Future work can focus on developing a novel neural network methodology that meets the requirements identified in this research (as well as other criteria) and optimising parameters to achieve the best outcomes.

ACKNOWLEDGEMENTS

We acknowledge that there are no funding sources for this work.

REFERENCES

[1] Shreerag Marar, Debabrata Swain, Vivek Hiwarkar, Nikhil Motwani and Akshar Awari "Predicting the occurrence of Parkinson's Disease using various Classification Models" 2018, IEEE. https://doi.org/10.1109/ICACAT.2018.8933579

[2] Mehrbakhsh Nilashi, Othman Ibrahim & Ali Ahani "Accuracy Improvement for Predicting Parkinson's Disease Progression" 2016, Scientific Reports.

[3] Srishti Grover, Saloni Bhartia, Akshama, Abhilasha Yadav Seeja K. R. "Predicting Severity Of Parkinson's Disease Using Deep Learning" 2018, Elsevier.

[4] Max A. Little, Member, IEEE, Patrick E. McSharry, Eric J. Hunter, Jennifer Spielman, and Lorraine O. Ramig "Suitability of Dysphonia Measurements for Telemonitoring of Parkinson's Disease" 2009, IEEE. https://doi.org/10.1038/npre.2008.2298.1

[5] C. Okan Sakar & Olcay Kursun "Telediagnosis of Parkinson's Disease Using Measurements of Dysphonia" 2009, Springer.

[6] Pei-Fang Guo, Prabir Bhattacharya and Nawwaf Kharma "Advances in Detecting Parkinson's Disease" 2010, Springer.

[7] Dery Avci and Akif Dogantekin "An Expert Diagnosis System for Parkinson Disease Based on Genetic Algorithm Wavelet Kernel-Extreme Learning Machine" 2016, Hindawi.

[8] Ali H. Al-Fatlawi, Mohammed H. Jabardi, Sai Ho Ling, "Efficient Diagnosis System for Parkinson's Disease Using Deep Belief Network" 2016, Elsevier https://doi.org/10.1109/CEC.2016.7743941

[9] Salama A. Mostafa, Aida Mustapha, Mazin Abed Mohammed, Raed Ibraheem Hamed, N. Arunkumar, Mohd Khanapi Abd Ghani, Mustafa Musa Jaber, Shihab Hamad Khaleefah "Examining multiple feature evaluation and classification methods for improving the diagnosis of Parkinson's disease" 2018, Elsevier.

[10] Mehrbakhsh Nilashi, Othman Ibrahim, Hossein Ahmadi, Leila Shahmor-adi, Mohammadreza Farahmand "A hybrid intelligent system for the prediction of Parkinson's Disease progression using machine learning techniques" 2017, Elsevier.

[11] Abdullah Caliskan, Hasan Badem, Alper Baştürk Mehmet Emin Yüksel "Diagnosis Of The Parkinson Disease By Using Deep Neural Network Classifier" 2017, IUJEEE.

[12] Salim Lahmiri, Debra Ann Dawson, Amir Shmuel "Performance of machine learning methods in diagnosing Parkinson's disease based on dysphonia measures" 2017, Springer.

[13] K.Gnana Sheela and S.N.Deepa "Review on Methods to Fix Number of Hidden Neurons in Neural Networks" Hindawi Publishing Corporation, Mathematical Problems in Engineering, volume 2013,Article ID 425740,11pages . https://doi.org/10.1155/2013/425740

[14] Postuma, R. & Montplaisir, J. Predicting Parkinson's disease-why, when, and how? Parkinsonism & related disorders 15, S105–S109 (2009).

[15] Das, R. A comparison of multiple classification methods for diagnosis of Parkinson disease. Expert Systems with Applications 37, 1568–1572 (2010).

[16] Ishihara, L., and Brayne, C., A systematic review of depression and mental illness preceding Parkinson’s disease. Acta Neurol. Scand. 113(4)211–220, 2006. doi:10.1111/j.1600-0404.2006.00579.x.

[17] W. Froelich, K. Wróbel, and P. Porwik, "Diagnosing Parkinson’s disease using the classification of speech signals," Journal of Medical Informatics & Technologies, vol. 23, pp. 187-194, 2014.

[18] B. E. Sakar, M. E. Isenkul, C. O. Sakar, A. Sertbas, F.Gurgen, S. Delil, H. Apaydin, O. Kursun, "Collection and Analysis of a Parkinson Speech Dataset with Multiple Types of Sound Recordings", IEEE Journal of Biomedical and Health Informatics, vol. 17, no. 4, pp. 828-834, July 2013.https://doi.org/10.1109/JBHI.2013.2245674

[19] H. Badem, A. Caliskan, A. Basturk, M. E. Yuksel, "Classification and Diagnosis of the Parkinson Disease by Stacked Autoencoder", 10th International Conference on Electrical and Electronics Engineering, Bursa, Turkey, 2016, pp. 499-502.

[20] Benba A., Jilbab A. Hammouch A., “Hybridization of best acoustic cues for detecting persons with Parkinson's disease”, 2014 Second World Conference on Complex Systems (WCCS), Agadir, 2014, pp. 622-625.

[21] Satyabrata Aich, Hee-Cheol Kim and Mangal Sain “A Supervised Machine Learning Approach Using Different Feature Selection Techniques on Voice Datasets for Prediction of Parkinson’s disease” 2018 ICACT.

[22] D. G. Standaert, M. H. Saint-Hilaire, C. A. Thomas "Parkinson’s Disease Handbook", American Parkinson Disease Association, New York, USA, 2015.

[23] C. A. Doukim, J. A. Dargham, and A. Chekima, “Finding the number of hidden neurons for an MLP neural network using coarse to fine search technique,” in Proceedings of the 10th International Conference on Information Sciences, Signal Processing and Their Applications (ISSPA’10),pp.606–609,May 2010.

[24] J. Zhang and A. J. Morris, “A sequential learning approach for single hidden layer neural networks,” Neural Networks, vol. 11, no.1,pp.65–80,1998.

[25] K.Shibataand Y.Ikeda, “Effect of number of hidden neurons on learning in large-scale layered neural networks” in Proceedings of the ICROS-SICE International Joint Conference 2009 (ICCASSICE’09), pp.5008–5013,August 2009.

[26] Y. Liu, J. A. Starzyk, and Z. Zhu, “Optimizing number of hidden neurons in neural networks,” in Proceedings of the IASTED International Conference on Artificial Intelligence and Applications (AIA’07), pp.121–126, February 2007.

[27] B. M. Bot, C. Suver, E. C. Neto, M. Kellen, A. Klein, C. Bare, M. Doerr, A. Pratap, J. Wilbanks, E. R. Dorsey et al.,“The mPower study, Parkinson disease mobile data collected using research kit,” Scientific data, vol. 3, p. 160011, 2016. https://doi.org/10.1038/sdata.2016.1